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IMAGE FUSION WITH EDGE PRESERVING SMOOTHING FILTER

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Abstract- This paper introduces fast and effective fusing of images through merging of multiple images for creating a highly information fused image .Here the edge preserving smoothing filter is used as guided filter. The fusion criterion is to minimize the different error between the fused image and input image The proposed method is based on two scale decomposition of image into a detail layer capturing small scale details and a base layer containing large scale variations in intensity. This method make full use spatial consistency for fusion of base and detail layer by using guided filter based weighted average technique.

Index terms-Guided filter, Two sacle decomposition,

I. INTRODUCTION

The utility of digital display is common for displaying gadgets. Therefore the input images captured are not good in brightness and contrast. To improve this image enhancement is normally required to improve the low brightness images various kinds of techniques are preferred . Image fusion is one of them.

Image fusion technique is to combine same scene of different images to form single image by enhancing the quality of image[1] . Interpretability or perception of image is improved by image enhancement . Image processing system may require both high spatial and high spectral information in a single image . While capturing the image capturing device are not capable with fine quality hence additional image processing required .Some of the image fusion techniques like multiscale image fusion [5]and data driven image fusion[6] are capable of preserving the information of source these methods during fusion process they produce brightness and color distorations. To make spatial context usefull we use optimization fusion approach examples are generalized random walks[3] and markov random fields[11] . Spatially smooth and edge align weights are estimated by using energy function and source images are fused by weighted average pixel values .Optimization methods have limitations that is inefficiency since for global optimal solution they require multiple iterations and another drawback is these methods over smooth the weighted results

To solve the problem above the proposed method is image fusion with guided filtering .The proposed fusion method advantages are

The method of this paper is fast two scale method to fuse which does not depend on the specific decomposition of images with simple average filter

The method is proposed for the construction of the weights to combine spatial context and pixel saliency for fusion of image. Guided filter is used as a local filter instead of using optimization method for image fusion

The main role of this paper is two measures that is spatial consistency and pixel saliency .These two measures are controlled by adjusting the parameters of guided filter

GUIDED IMAGE FILTERING

Recently edge preserving filter[12],[13] is active research topic .Edge preserving algorithm is used to detect the edges of the images .Edge detection method were images of various area are detected .Using this technique noise can be reduced and performance of the image quality can be enhanced. Some of the edge preserving smoothing filters which avoid ringing artifacts such as guided filter[12], weighted least squares [13]and bilateral filter[14] and the edges are not blured. The recently proposed edge preserving filter among them is guided filter

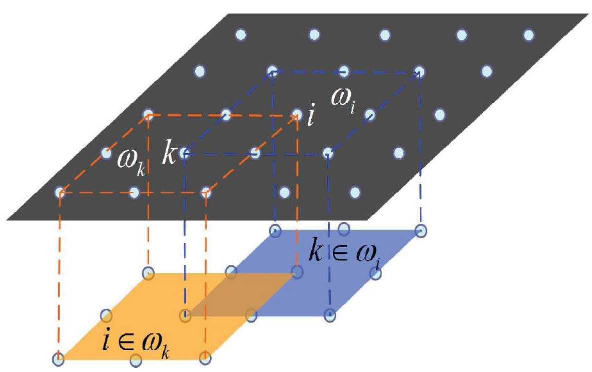

Fig 1 window choice illustration

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Guided filter is based on local linear model , applications such as image matting, up sampling and colorization for which it is qualified. For image fusion guided filter is first applied in this paper.

Guided filter assumes that in a local window ω_k centered at pixel k with filtering output O is linear transformation of the guidance image I

$$O_i = a_k I_i + b_k \ \forall i \in \omega_k$$

Where ω_k is a square window of size $(2r+1)\times(2r+1)$.The linear coefficients a_k and b_k are constant and the output image O and the input image P where the squared difference between them is minimized

$$E(a_k,b_k) = ((a_k I_i + -p_i)^2 + \epsilon a_k^2)$$

Where ϵ is regularization parameter .Linear regression is used to solve the coefficients a_k and b_k

$$a_k = \frac{\frac{1}{|\omega|}\sum_{i\in\omega_k} I_i P_i - \mu_k \bar{P}_k}{\delta_k + \epsilon}$$

$$b_k = \bar{P}_k - a_k \mu_k$$

μ_k and δ_k are mean and variance of I , $|\omega|$ is number of pixels in ω_k

and P_k is the mean of P in ω_k .The output image can be calculated as

$$O_i = a_i I_i + b_i$$

Where $\bar{a}_i = \frac{1}{|\omega|}\sum_{k\in\omega_i} a_k$, $\bar{b}_i = \frac{1}{|\omega|}\sum_{k\in\omega_i} b_k$

$G_{r,\epsilon}(P, I)$ is guided filter operation where r and ϵ are the parameters of filter size and blur degree .I refers to guidance image and P refers to input image .Further guided filtering operation is performed on red ,green and blue channels when the input image is color

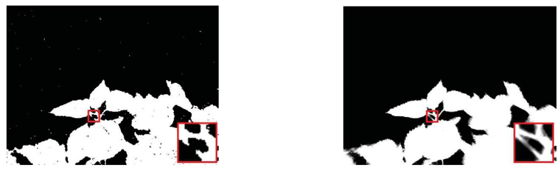
$$O_i = a_k^T I_i + b_k \ \forall i \in \omega_k$$

Where a_k is 3x1 coefficient vector and I_i is 3x1 color vector

$$a_k = (\textstyle\sum_k + \in U)(\frac{1}{|\omega|}\sum_{i\in\omega_k} I_i p_i - \mu_k \bar{P}_k)$$

$$b_k = \bar{P}_k - a_k^T \mu_k$$

$$O_i = \bar{a}_i^T I_i + \bar{b}_i$$



a b

Fig 2 Examples of guided filtering.(a) represents input image (b) shows guided filter output image

fig 2(a) which is noisy with and not aligned with object boundaries after undergoing guided filter operation the output image is shown in 2(b)

a b

Fig3 shows color image (a) represents the input image (b) represents the guided filter output image it will preserve the strong edges and can blur the image details

II. IMAGE FUSION WITH GUIDED FILTER

The proposed method guided filter fusion is shown in figure .Two scale representation of the average filter is utilized .Then, by using guided filtering weighted average method base and detail layers are fused

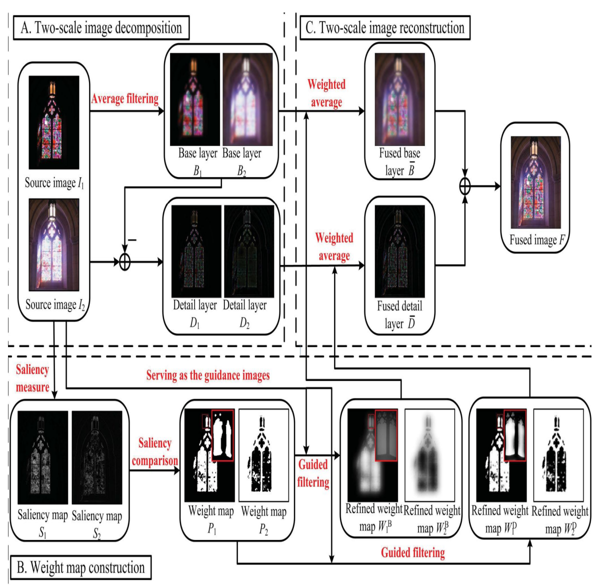


Fig 3 shows the proposed method using the concept Image fusion with guided filtering

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A. Two scale image decomposition

Decomposition of the source images by using average filter into two scale representation . For each source image the base layer is obtained

$$Bn=In * Z$$

Z is average filter , In is nth source image and size of average filter is 31x31.After obtaining base layer ,the detail layer is obtained by substracting base layer from the source image

$$Dn=In - Bn$$

Base layer contains large scale variations and detail layer contains small scale variations

B. Weight Map Construction With Guided Filtering

To construct the weighted map .Laplacian filtering is applied first to obtain the high pass image Hn to each source image

$$Hn= In * L$$

L is 3x3 Laplacian filter . Hn is local average absolute value which is used to construct saliency maps Sn.

$$Sn=|Hn|*grg,\sigma g$$

Where g is a Gaussian low-pass filter of size (2rg + 1) (2rg + 1) and the parameters rg and σg are set 5.The saliency maps are compared to determine weight maps

$$PnK=\begin{cases}1 & \text{if } S_n^k = \max(S_1^k, S_2^k, \dots, S_N^k)\\ 0 & \text{otherwise}\end{cases}$$

Where N is number of source images , Skn is the saliency value of the pixel k in the nth image

The weighted maps are noisy and the object boundries are not aligned which produces artifacts were the images are fused .The problem is solved by using spatial consistency which means that two adjacent pixels were brightness or color is similar. While formulating an energy function spatial consistency based fusion approach is used ,for encoding pixel saliencies are used in function and enforced by edge align weights. To obtain desire weights the energy function can be minimized globally and optimization methods are inefficient.

The proposed method is in alternative to optimization based method . guided filter is performed weight map pn with source In which is used as guidance image

$$WnB=Gr1,€1(Pn,In)$$

$$WnD=Gr2,€2(Pn,In)$$

Where r1, r2, €1, €2 are the parameters of the guided filter WnB and WnD are the resulting Weights maps of the base and detail layer .The values of the N weight maps are normalized and they sum to one at each pixel k

In order to avoid artificial edges the base layers are spatially smooth and corresponding weights are also spatially smooth and for the detail layer sharp and edge align weights are produced .Therefore for base layer large blur degree and large filter size is preferred and for detail layer small filter size and small blur degree

BLENDING METHOD

Undesirable intensity discrepancies are observed in most of the neighbouring edge images. Even though cross-correlation is perfect in eye there is change in the intensity variations .Blending or feathering algorithm is applied in order to eliminate such effects

The visual quality of the the composite image can be improved by the blending method .Images are placed next to each other in composite image .An adequate size of empty composite image is created first. Spiral-like pattern is created for the images which are placed starting from the central image

The composite image consists of each image cross-correlation between composite image and the new image is used to determine the position and the blending algorithm is applied .

In figure The composite image and the new image is overlapped .For the overlapped region to calculate contribution of composite image for every pixel and new image image blending algorithm is applied

For every size and shape of overlap a look up table is created and is normalised for the proportion of intensities used for the two regions which is overlapped for generating the composite image

Fig which the overlapped image weighting (α)

The blending image consists of pixel

$$N(x, y)= \alpha I(x, y)+(1- \alpha)C(x, y)$$

Where C(x, y) is composite image , I(x, y) is the new image pixel, N(x, y) new composite image pixel

To improve the cross correlation and and to minimize the intensity variation blending algorithm is used

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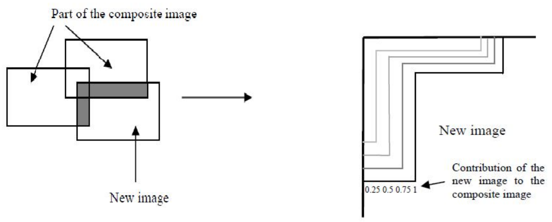

Fig 4 procedure for blending intensities of overlapping images

C. Two scale image reconstruction

Two steps are considered for two scale image reconstruction

By weighted average technique the base and detail layer of different source images are fused

$$\bar{B} = \sum_{n=1}^{N} W_n^B B_n$$

$$\bar{D} = \sum_{n=1}^{N} W_n^D D_n$$

After the base and detail layers of different source images are fused the blending operation is performed to remove the intensity variations and the overlapping regions

The obtained images after undergoing blending operation will have improved visual image quality

F is obtained by combining fused base layer and fused detail layer

$$F = \bar{B} + \bar{D}$$

III. **Experiments and discussion**

Using Fusion quality metrics in order to assess fusion performance of different methods

Normalized mutual information QMI: It is an information theory based metrics .It may bias the source image measure with highest entropy and it is unstable is the problem with information theory based metric .Hossny et al had modified information theory based to normalized mutual information

where H(A), H(B) and H(F) are the marginal entropy of A, B and F, and MI(A, F)is the mutual information between the source image A and the fused image F.

$$MI(A, F) = H(A) + H(F) - H(A, F)$$

where H(A, F) is the joint entropy between A and F, H(A) and H(F) are the marginal entropy of A and F, respectively, and MI(B,F) is similar to MI(A, F).

The quality metric measures the fusion performance that is original information how well it is preserved

Yang et al.'s metric QY : For fusion assessment it uses structural similarity based image quality measure .which is defined as

$$QY = \begin{cases} \lambda_\omega SSIM(A_\omega, F_\omega) + (1-\lambda_\omega) SSIM(B_\omega, F_\omega), \\ \quad \text{if } SSIM(A_\omega, B_\omega|\omega) \ge 0.75 \\ \max\{SSIM(A_\omega, F_\omega), SSIM(B_\omega, F_\omega)\}, \\ \quad \text{if } SSIM((A_\omega, B_\omega|\omega) < 0.75 \end{cases}$$

Where ω is a window of size 7x7, F is fused image and A,B are the input images, SSIM is the structural similarity λ_ω is calculated as follows

$$\lambda_\omega = \frac{s(A_\omega)}{s(A_\omega)+s(B_\omega)}$$

Where $s(A_\omega)$ and $s(B_\omega)$ are the variance of source images A and B within the window ω, respectively. QY measures how well the source information is preserved

Cvejic et al.'s metric Qc is calculated as follows

$$Qc = \mu(A_\omega, B_\omega, F_\omega) UIOI(A_\omega, F_\omega)$$

$$+(1-\mu(A_\omega, B_\omega, F_\omega)) UIQI(B_\omega, F_\omega)$$

Where $\mu(A_\omega, B_\omega, F_\omega)$ is calculated

$$\mu(A_\omega, B_\omega, F_\omega) = \begin{cases} 0, & \text{if } \frac{\sigma_{AF}}{\sigma_{AF}+\sigma_{BF}} < 0 \\ \frac{\sigma_{AF}}{\sigma_{AF}+\sigma_{BF}}, & \text{if } 0 \le \frac{\sigma_{AF}}{\sigma_{AF}+\sigma_{BF}} < 1 \\ 1, & \text{if } \frac{\sigma_{AF}}{\sigma_{AF}+\sigma_{BF}} > 1 \end{cases}$$

σ_{AF} and σ_{BF} are the covariance between A,B and F and UIQI refers to universal image quality index and

Qc quality metric estimates how well the source information is preserved in fused image while minimizing the amount of distortion

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Analysis of free parameter

Using the separate image database objective fusion performances are analyzed with influences of different parameters. Using average values of quality metrics that is information theory based, structural similarity based image quality measurement and universal image quality index the fusion performance are evaluated. While analyzing r1 other parameters are set to Є1=0.3, r2=7 and Є2=10^-6 and again when analyzing Є1 other parameters are set to r1=45,r2=7 and Є2=10^-6. The same way Є2 and r2 are analyzed. It is preferred to have big filter size r1 and blur degree Є1.when filter size r2 is too large or too small the fusion performance will be worse for fusing the detail layer .The default parameters are set to r1=45, Є1=0.3, r2=7 and Є2=10^-6 . To obtain good results for images setting fixed parameter because for exact parameter choice the GFF method does not depend

IV. **Results obtained**

Fig5 which represents examples of guided filtering. (a) input image with noisy and not aligned with object boundaries with SNR=30dB and (b) represents guided filter image where noisy pixels are removed and is aligned with object boundaries with filtering size 5

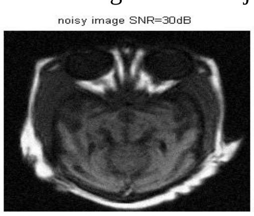


fig5(a)

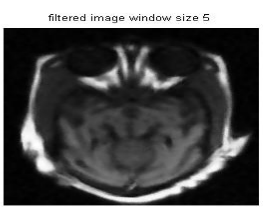
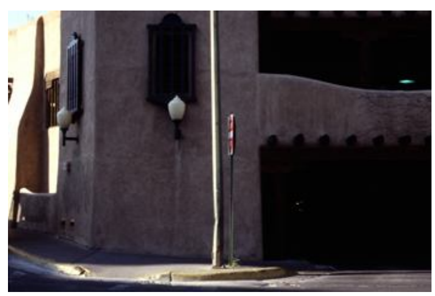


fig5(b)

Fig 6 shown below are the examples of guided filtering. (a) which is input image and (b) which is the guided filter output image while preserving the strong edges and can blur the image details


a b

fig 7 below are the results obtained for image fusion with guided filtering



Input image1

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input image 2

Output image fusion with guided filtering

V. Comparison with other fusion methods

Image quality index	SWT	PCA	Proposed method
CORR	0.9268	0.9051	0.9357
LMSE	2.1612	1.5515	1.0925
MAE	0.2353	0.2505	0.223
MI	1.2228	1.3435	0.8314
MSSIM	0.9987	0.9982	0.9999
PFE	33.543	37.2626	32.3439
PSNR	37.057	37.0221	37.149
QI	0.3164	0.3665	0.5133
RMSE	12.9055	13.0098	12.6325
SC	1.8592	2.1606	1.5960
SSIM	0.9914	0.9892	0.9918
VIF	0.2206	0.2621	0.9105
dent	0.3497	0.3650	0.9913

From the above table it shows that comparing the proposed method with other fusion method such as stationary wavelet transform (SWT) and principal component analysis (PCA)

Quality metric such as mutual information which refers to how well the source information is transferred to fused image .However it does not measure complementary information is well preserved from different source images .QI which refers to universal image quality index the table shown above refers that the proposed method has good quality index then other two fusion methods and SSIM measure also is better than comparing other two methods

CONCLUSION

Image fusion with guided filtering is represented in this paper .To get two scale representation it utilizes the average filter .In order to get weight optimization a strong correlation is used between neighbourhood pixels. comparing with other fusion method it can well preserve the complementary information and is qualified for real application .Further research is going on for adaptively choosing the parameters of guided filter

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